AN ASSESSMENT ON LAND USE AND LAND COVER CHANGES IN KYAING TONG TOWNSHIP, MYANMAR

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Abstract

Land use and land cover (LULC) classification using Satellite Imagery is a noteworthy approach to monitor changes in Kyaing Tong Township. Using remote sensing techniques (RS) and Geographic information Systems (GIS), LULC is classified into six categories: agriculture land, bare land, built-up area, dense forest, sparse forest and water-body. The principal aim of this paper is to identify the spatial distribution of LULC classes within time-span and assess the changes patterns of its class. To retrieve attribute data, maximum likelihood classification algorithm is used. Ground truth and remote sensing data were interpreted by Kappa coefficient, the resulted values show over 85 percent which is found near perfect satisfactory agreement. Likewise, to know clearly the changes, volume of change method is analysed, it points out that the trend of change is going to both increased and decreased. The positive changes or the gain area were sparse forest 5.21 percent agriculture land with 4.72 percent and build-up area with 1.81 percent whereas, the negative changes or the loss area were dense forest with 10.10 percent, bare-land with 0.89 percent and water-body with 0.75 percent. As the technical skill advance day by day, the digital aera of LULC can be acquired from the remote sense technology. Therefore, the application of GIS/RS methods are the best estimation of spatial and temporal changes in land use and land cover study.

Keywords: LULC, GIS, RS, maximum likelihood, distribution, changes

Introduction

Land use is the characteristic of complex anthropogenic activities that change the surface of the land whereas land cover is the physical and biological cover of the land surface (Foley et al. 2005). However, both the terms land use and land cover are closely related to interchangeable (Simon Foteck Fonji et al., 2014, Chaudhary et al., 2008, and Foteck Fonji et al.). Therefore, this study utilized Landsat Imageries for LULC data source.

There are several types of land use and land cover classified category in the world. However, the classification system is different to the scholar's views according to the respective environmental region. The classification type should be consistent with the requirements of user. In this study LULC classification system is based on the Anderson classification: agriculture land, bare land, built-up area, dense forest, sparse forest and water-body (Table 1).

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Table 1 LULC Classification System by using the Remote Sensing Data

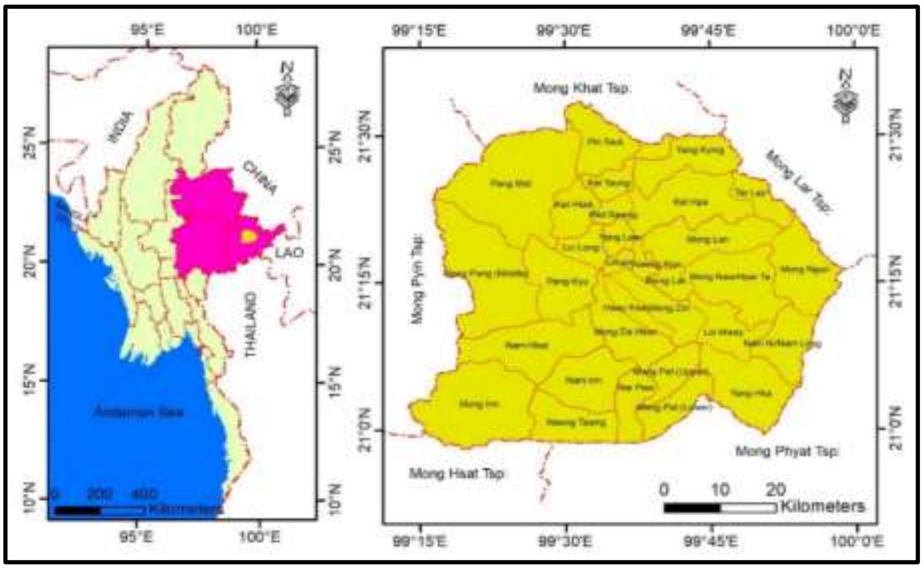
LULC Classes	Description
Agriculture Land	*Le* Land, *Ya* Land, Garden Land
Bare Land	Open Space, Vacant Land, Bare Soil
Build-up Area	Settlement, Air Field
Dense Forest	Ever Green Forest, Permanent Forest,
	Deciduous Forest, Mixed Forest
Sparse Forest	Grass land, Pasture, Bushes
Water-body	Lake, Pond, River, Stream, Reservoir

Source: Based on Anderson, J.R., Land Use and Land Cover Classification System for Use with Remote Sensor Data

Research Area

The study area, Kyaing Tong Township, is situated in Shan State (East) and belongs to the eastern of Myanmar. It is located between latitudes 20º 58′ N and 21º 35′ N and also between Longitude 99º 16′ E and 99º 58′ E. The area is covered by 3,783.31 square kilometres or 1,460.74 square miles. The elevation is 826 meters (2,710 feet) above sea level. Kyaing Tong Township is bounded on the north by Mong Khat Township, on the north-east by Mong Lar Township, on the southeast by Mong Phyat Township, on the northwest by Mong Hsat Township and on the west by Mong Pyin Township respectively. The length from east to west is about 62 km and (63 miles) width from north to south. It has nearly compact in shape (Figure 1).

Physiographically, Kyaing Tong Township comprises mountain ranges in the peripheral margin and depression in the centre of its township forming irregular and diverse nature of topography. The highest peak is Loiphi Taung (2,263 m or over 7,500 feet). The general inclination of slope is facing from south to north. Based on the relief, the drainage pattern is typically distributed in the centre of the study area. The stream flows to the north direction accordingly. The significant stream is Nam-Khin *Chaung* which flow through near Kyaing Phaung Village, Kyaing Tong Town as flowing to the north orientation. The town or the densest settlement area is located in the concentric area of its township. Thus, the settlement pattern is more tremendous and concentrated on the levelling plain area than the peripheral rugged region.



Source: Myanmar Information Management Unit (MIMU_2019)

Figure 1 Location of the Study Area

Aims and Objectives

The main goals are to identify the spatial distribution of LULC classes over a decade period and assess the changes pattern in Kyaing Tong Township. The objectives are to investigate the background of the LULC change, classify the respective LULC spatial extent with temporal interval to which conversion occurred, analyse the changing pattern of LULC classes and find out the volume of change in each LULC category.

Materials and Methods

Materials

In the LULC classification system, the acquisition of remote sensing information from Satellite Imageries were applied by geospatial technology: Geographic Information System (GIS) with a Spatial Reference System (SRS) of WGS 1984 UTM Zone 47º N. LULC classification source is generated from Landsat 5 (Thematic Mapper (TM) and Landsat 8 (The Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)) with the time frame of February and March in two different years, 2011 and 2021. Both of these imageries with multi-spectral band were operated from bands 1 to 7 in order which having mostly spatial resolution 30 meters each. According to the study area, Landsat data were obtained from the Worldwide Reference System (WRS) Path_131 and Row_45 (Table 2). The acquisitions of remote sensing images were downloaded and derived from the United States Geological Survey (USGS) earth explorer website (http://earthexplorer.usgs.gov/). Time has taken in choosing and acquiring a good quality of radiometric resolution without cloud cover or cloud-clear images. If the image is covered with cloud it could be confused with the real object on the earth surface and made a complex phenomenon to identify LULC classes.

In addition, Digital Elevation Model (DEM), mounted on Shuttle Radar Topography Mission (SRTM), was extracted from the relief map where mountain range and depression are located, and retrieved the drainage pattern where river or stream are both of the relief and drainage pattern supported in selecting for correct training sample location in the study area.

Table 2 Description of the Satellite Image used in the Study

Satellite	Sensor	Date acquired	Bands used	Wavelength (μm)	Spatial Resolution	WRS Path/Row
Landsat 5	Thematic Mapper (TM)	February 8, 2011	Band 1 Visible blue	0.45 - 0.52	30 m	131/45
			Band 2 Visible green	0.52 - 0.60	30 m	
			Band 3 Visible red	0.63 - 0.69	30 m	
			Band 4 Near-Infrared	0.76 - 0.90	30 m	
			Band 5 Near-Infrared	1.55 - 1.75	30 m	
			Band 6 Thermal	10.40 - 12.50	120 m	
			Band 7 Mid-Infrared	2.08 - 2.35	30 m	
Landsat 8	The Operational Land Imager and Thermal Infrared Sensor (OLI_TIRS)	March 7, 2021	Band 1 Coastal / Aerosol	0.433 - 0.453	30 meter	131/45
			Band 2 Visible blue	0.450 - 0.515	30 meter	
			Band 3 Visible green	0.525 - 0.600	30 meter	
			Band 4 Visible red	0.630 - 0.680	30 meter	
			Band 5 Near-infrared	0.845 - 0.885	30 meter	
			Band 6 Short wavelength infrared	1.56 - 1.66	30 meter	
			Band 7 Short wavelength infrared	2.10 - 2.30	60 meter	

Source: usgs.gov

Moreover, Universal Transverse Mercator (UTM) map with the scale of 1:50,000 was applied in this research. Nine topo-sheets were used such as 2199_06, 2199_07, 2199_08, 2199_10, 2199_11, 2199_12, 2199_14, 2199_15 and 2199_16. Based on those based map, vector point of settlement's (town or village) location was created as a point algorithm and displayed on the map for ground truthing where the settlement position was. These function helps the right training sample of LULC classification as well.

Methods

In the LULC identification process, the solely geospatial techniques: GIS software 10.4.1 was operated in this research. The general methodology is described in Figure (2). To generate the LULC classes, True Colour Composite was used as a training sample (Trolle et al., 2019). Thus, the total training sites are collected 1,037 and 1,787 polygon samples with a variety of LULC classes in 2011 and 2021 to capture spectral variability respectively. This process needed a number of training sites for all the classes spread across the study area. At that time, Maximum Likelihood Classifier was applied to extract LULC classes information from satellite images and declare training sample to be transformed as respective LULC classes. Then, the information from Satellites Imageries were classified into six LULC classes: agriculture land and bare land, build-up area, dense forest, sparse forest, water-body (Table 1).

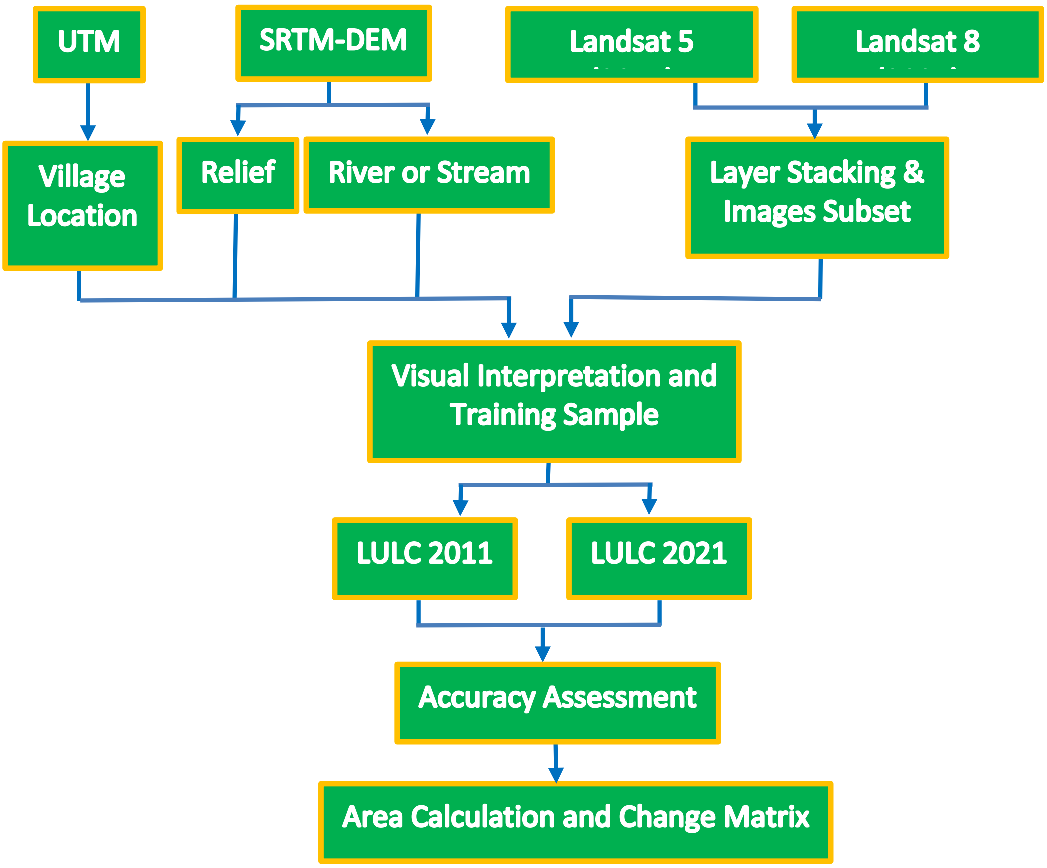


Figure 2 Methodological Workflow

Results and Discussion

Field Survey and Accuracy assessment

In the case of field survey, the wide-spread ongoing global pandemic of coronavirus disease 2019 makes a tough period for personally ground truthing. Instead of this activity, Google Earth Pro helps in checking the consistent between the data actually measured in the field and the classified remote sensed images.

Accuracy assessment is a crucial role in any LULC classification. It can be defined as the number of pixels which are correctly classified into the sum of all pixels. It is estimated by evaluating overall accuracy along with kappa coefficient. These values are calculated by using confusion matrix (Sharma, J. et al., and Lillesand et al., 2004). By using the following methods, the results are prescribed in Table 3-A, 3-B, 4-A and 4-B.

$$\text{Overall Accuracy} = \frac{Total\ Number\ of\ Correctly\ Classified\ Pixels\ (Diagonal)}{Total\ Number\ of\ Reference\ Pixels} \text{ x } 100$$

$$\text{User Accuracy} = \frac{Number\ of\ Correctly\ Classified\ Pixels\ in\ each\ Category}{Total\ Number\ of\ Classified\ Pixels\ in\ That\ Category\ (The\ Row\ Total)} \text{ x } 100$$

$$\text{Producer Accuracy} = \frac{Number\ of\ Correctly\ Classified\ Pixels\ in\ each\ Category}{Total\ Number\ of\ Reference\ Pixels\ in\ That\ Category\ (The\ Column\ Total)} \times 100$$

$$\text{Kappa Coefficient} = \frac{(TS \times TCS) - \sum(Column\ Total \times Row\ Total)}{TS^2 - \sum(Column\ Total \times Row\ Total)} \times 100$$

TS = Total number of specified pixel

TCS = Total number of correctly classified pixels

The application of accuracy assessment on **error matrix** was done by using stratified random sample number with 35 vector points each in 2011 and 2021 (Table 3-A, 3-B). Each category of LULC class was taken from the different sample points according to the different area enlargement. The greater area extent was collected from more sample points, conversely, the smaller sample points were plotted on smaller area extent. The order of greater to smaller area size in six classes of LULC are sparse forest, dense forest, agriculture land, bare land, build-up area and water-body. Those area extents are demonstrated in the same trend order area size in 2011 and 2021.

Table (3-A) Accuracy Assessment on Error Matrix in the Classified Images (2011)

Category	Agriculture Land	Bare Land	Build-up Area	Dense Forest	Sparse Forest	Water-body	Total User (Point)
Agriculture Land	7	1	0	0	0	0	8
Bare Land	0	5	0	0	0	0	5
Build-up Area	0	0	3	0	0	0	3
Dense Forest	0	0	0	8	1	0	9
Sparse Forest	0	0	0	2	4	0	6
Water-body	0	0	0	0	0	4	4
Total Producer (Point)	7	6	3	10	5	4	35

Source: Landsat 5 (2011)

Table (3-B) Accuracy Assessment on Error Matrix in the Classified Images (2021)

Category	Agriculture Land	Bare Land	Build-up Area	Dense Forest	Sparse Forest	Water-body	Total User (Point)
Agriculture Land	5	1	0	0	0	0	6
Bare Land	0	5	0	0	0	0	5
Build-up Area	0	0	4	0	0	0	4
Dense Forest	0	0	0	8	0	0	8
Sparse Forest	0	0	0	2	7	0	9
Water-body	1	0	0	0	0	2	3
Total Producer (Point)	6	6	4	10	7	2	35

Source: Landsat 8 (2021)

The tabulation of accuracies, which is **user accuracy** and **producer accuracy**, per individual LULC class are illustrated in Table 4-A and 4-B. Thus, the reflected pixel value of Satellite Images of LULC classes and the ground truth point from Google Earth Pro were checked how much consistency is. The **overall accuracy** is resulted 88.57% in both 2011 and 2021 each. **Kappa coefficient**, the final calculation of those reference pixels and correctly classified pixels (diagonal) is resulted 85.92 % in each time frame, 2011 and 2021 respectively. As the Cohen's Kappa coefficient interpretation, it is revealed that almost perfect agreement because the minimum of those satisfied agreement level is 85%.

Table (4-A) Producer and User Accuracy Assessment in Kyaing Tong Township (2011)

LULC Category	Reference Total	Classified Total	Correct Number	Producer Accuracy (%)	User Accuracy (%)
Agriculture Land	8	7	7	100.00	87.50
Bare Land	5	6	5	83.33	100.00
Build-up Area	3	3	3	100.00	100.00
Dense Forest	9	10	8	80.00	88.89
Sparse Forest	6	5	4	80.00	66.67
Water-body	4	4	4	100.00	100.00

Source: Landsat 5 (2011)

Table (4-B) Producer and User Accuracy Assessment in Kyaing Tong Township (2021)

LULC Category	Reference Total	Classified Total	Correct Number	Producer Accuracy (%)	User Accuracy (%)
Agriculture Land	6	6	5	83.33	83.33
Bare Land	5	6	5	83.33	100.00
Build-up Area	4	4	4	100.00	100.00
Dense Forest	8	10	8	80.00	100.00
Sparse Forest	9	7	7	100.00	77.78
Water-body	3	2	2	100.00	66.67

Source: Landsat 8 (2021)

As mentioned above, the process of classification is based on the reflected and coloured value from the remote sensing images. As the similarity of colour-reflected-value with different ground truth object, the error of classification on LULC class might occurred. During the classification, the identification of LULC between an image and actual ground truth can be misclassified as agriculture land to bare land, dense forest to sparse forest and sparse forest to dense forest. Similarly, after the classification by maximum likelihood classifier, some of LULC class was misclassified as build-up area to sparse forest because the surrounded settlement area has green spaces such as growing agricultural crops and trees plantation. In some areas, bare land was also misclassified as water-body and build-up area because the reflection of those values is almost similarity.

LULC Distribution Pattern

The spatial and temporal distribution pattern of LULC classes were described in Figure 3 and Table 5. Those data were generated from Landsat imageries and used by supervised classifier for the time span between 2011 and 2021.

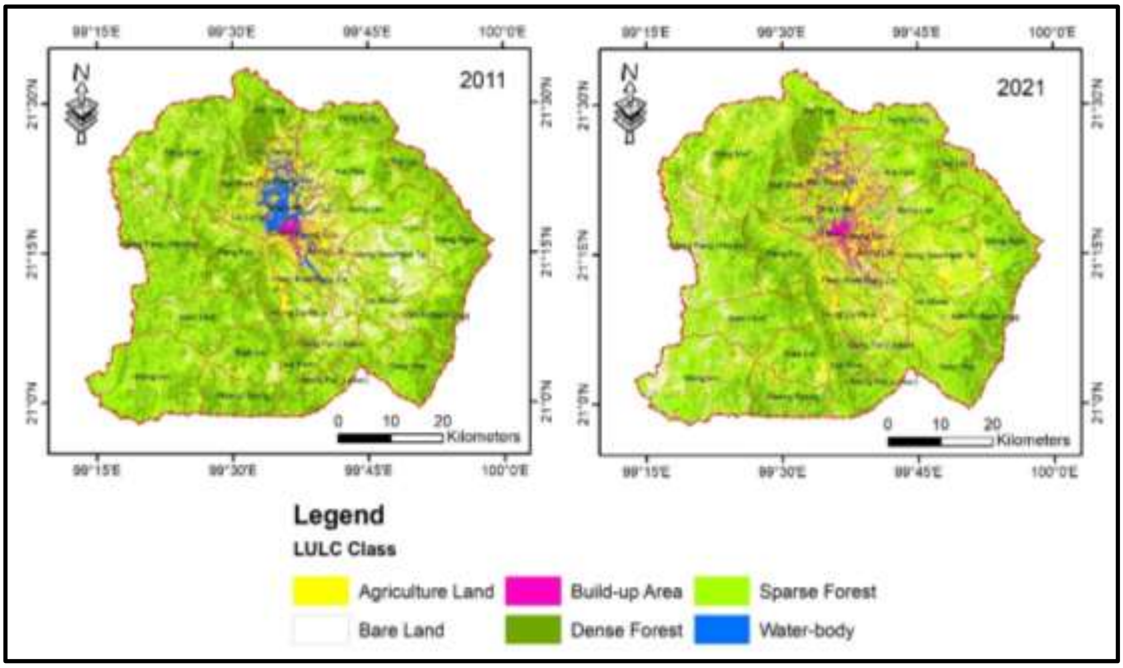
In 2011, the pattern of LULC classes were dominated by sparse forest 48.58% (1,838.09 sq. km), followed by dense forest 28.56% (1,080.63 sq. km), agricultural land was about 9.28% (350.92 sq. km), bare land was 9.14% (345.89 sq. km), built-up area covered 2.23% (84.50 sq. km) and water-body with 2.2% (83.27 sq. km) (Table 5). The striking feature and excessive amount of water-body (Figure 3_2011) was found the **temporary water-body which is the highly unusual rainfall in February** gathered in Kyaing Tong Plain area: Yang Law, Wut Sawng, Loi Long, Kat Taung and Kat Hpa village tracts. Those water-body area is mostly turned into agriculture land in 2021, and it is found as the original agricultural lands. However, the agriculture land area is grown with full of paddy and vegetable plantation, thus the reflected value of those plantation is appeared as sparse forest (light green) on the map (Figure 3_2021) as the reflected value of vegetable plantation is the same with sparse forest. Therefore, agriculture land in the Kyaing Tong Plain is similar to sparse forest because the reflected value of those plantation is the same as sparse forest.

Table 5 The Distribution of LULC Class in Kyaing Tong Township

No.	Category	2011		2021	
		Area (km)	Area (%)	Area (km)	Area (%)
1	Agriculture Land	350.92	9.28	529.32	13.99
2	Bare Land	345.89	9.14	312.36	8.26
3	Build-up Area	84.50	2.23	153.01	4.04
4	Dense Forest	1,080.63	28.56	698.43	18.46
5	Sparse Forest	1,838.09	48.58	2,035.34	53.80
6	Water-body	83.27	2.20	54.85	1.45
Total		3,783.31	100.00	3,783.31	100.00

Source: Landsat 5 and Landsat 8

In 2021, on the other hand, the observed pattern of LULC classes were mainly occupied by sparse forest which had the largest extent and shared 53.80% (2,035.34 sq. km) followed by dense forest 18.46% (698.43 sq. km), about 13.99% (529.32 sq. km) of the area covered by agricultural land, bare land covered 8.26% (312.36 sq. km), built-up area 4.04% (153.01 sq. km) and water-body 1.45% (54.85 sq. km) respectively (Table 5).



Source: Landsat 5 and Landsat 8

Figure 3 The Distribution Pattern of LULC Class in Kyaing Tong Township (2011 and 2021)

The spatial distribution of LULC classes in area expanse were disseminated the same trend between 2011 and 2021 (Figure 3). In the diffusion by alphabetical category, agriculture land was mainly occurred in the Kyaing Tong Plain: Yang Law, Wut Sawng, Loi Long, Kat Taung and Kat Hpa village tracts. Bare land was also found in Mong Pat, Kat Hpa, Mong Lan, Mong Naw/ Par Ta, Mong Zin, Loi Mway, Mong Pat (Upper) and Mong Pang (Middle) village tract. Build-up area was especially found in urban area and Mong Zing Village Tract. In addition, dense forest was discovered in Pin Mat, Pin Tauk, Kat Htaik, Yang Kying, Kat Hpa, Tar Lay, Mong Nyun, Nam Ni/ Nam Long, Yang Hka, Nar Paw, Mong Da Hkun, Nawng Tawng, Nam Inn, Mong Inn, Nam Hkat and Pang Kyu village tracts. Moreover, sparse forest was spread in Pin Mat, Pin Tauk, Kat Taung, Yang Kying, Kat Hpa, Tar Lay, Mong Nyun, Mong Lan, Mong Naw/ Hpar Ta, Loi Mway, Nam Ni/ Nam Long, Yang Hka, Mong Pat (Upper), Mong Pat (Lower), Nam Inn, Nar Paw, Mong Da Hkun, Nawng Tawng, Nam Inn, Mong Inn, Nam Hkat and Pang Kyu and Mong Pang (Middle) village tracts. Furthermore, water-body was occupied at Kat Taung, Wut Sawng, Yang Law and Loi Long, Mong Zin, Kat Hpa village tracts (Figure 3).

Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it in different times (Singh, 1989 and Jwan Al-doski, 2013). This is considered an important process in monitoring LULC because it provides quantitative analysis of the spatial distribution.

In the change detection portion, change matrix from the reference source Landsat 5 and Landsat 8 were analysed over ten years period between 2011 and 2021. Change matrix displays the key information of LULC. (Shalaby and Tateishi, 2007). The detail result of change matrix is shown in (Table 6).

In the overall changed pattern in 2011-2021-year period, statistically the increased areas were agriculture land from 350.92 sq. km to 529.34 sq. km, build-up area from 84.54 sq. km to

153.00 sq. km, and sparse forest from 1,812.24 sq. km to 2,035.32 sq. km. Conversely, the decreased areas were bare land 345.93 sq. km to 312.35 sq. km, dense forest 1080.56 sq. km to 698.47 sq. km and water-body from 109.15 sq. km to 54.84 sq. km (Table 6).

The bold numbers or highlighted grid cells are identified the stable area or no changed area for respective LULC classes: agriculture land with 216.99 sq. km, bare land with 101.53 sq. mi, build-up area withy 32.11 sq. km, dense forest with 551.37 sq. km, sparse forest with 1,363.95 sq. km and water-body with 15.41 sq. km (Table 6).

Table 6 LULC Changes Matrix between 2011 and 2021 in Kyaing Tong Township.

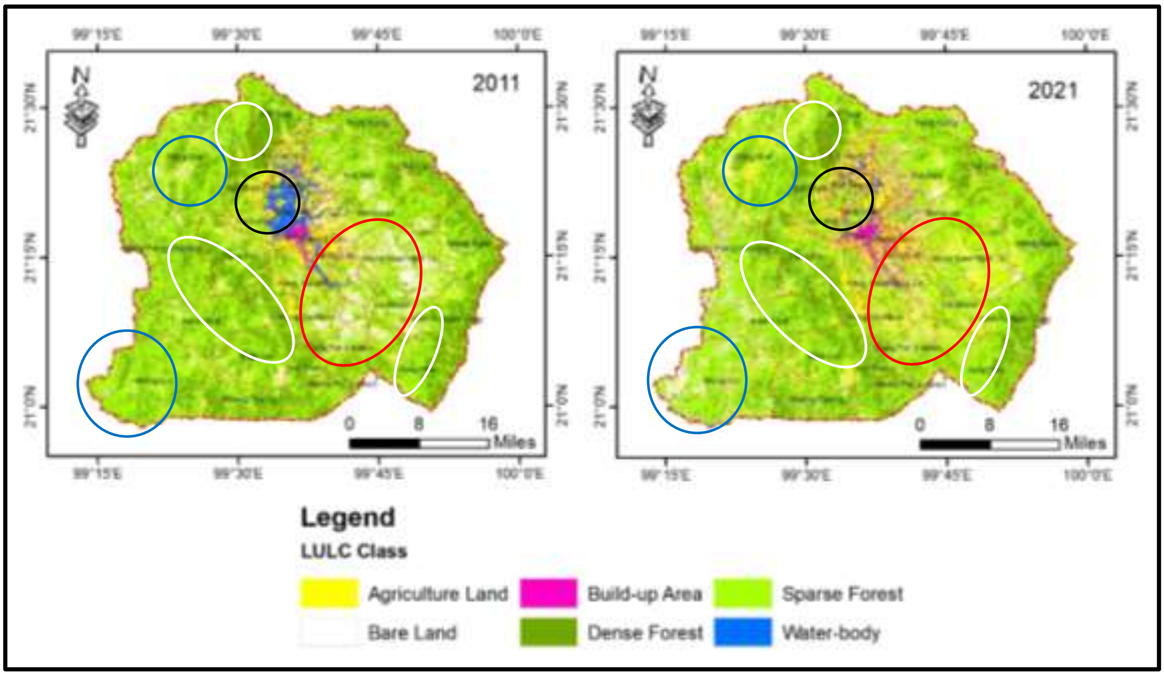
LULC Class		2021 Area in square kilometer						
		Agriculture Land	Bare Land	Build-up Area	Dense Forest	Sparse Forest	Water-body	Total 2011
2011 Area in square kilometer	Agriculture Land	216.99	31.12	30.00	4.51	56.70	11.61	350.92
	Bare Land	145.77	101.53	13.91	2.43	78.00	4.29	345.93
	Build-up Area	23.64	7.16	32.11	0.82	16.63	4.14	84.51
	Dense Forest	24.09	20.37	12.40	551.37	459.79	12.54	1,080.56
	Sparse Forest	102.64	149.84	49.89	139.07	1,363.95	6.85	1,812.24
	Water-body	16.21	2.32	14.70	0.26	60.25	15.41	109.15
	Total 2021	529.34	312.35	153.00	698.47	2,035.32	54.84	3,783.31

Source: Landsat 5 and Landsat 8

Similarly, the detailed changes patterns from individual LULC class to another respective single class is shown in Table 6. Between 2011 and 2021, the most striking changes area in each category to another in alphabetical order were agriculture land to sparse forest 56.70 sq. km, bare land to agriculture land 145.77 sq. km, build-up area to agriculture land 23.64 sq. km, dense forest to sparse forest 459.79 sq. km, sparse forest to bare land 149.84 sq. km and water-body to sparse forest 60.25 sq. km.

In the spatial changes pattern, the area changes from one LULC class to another were dense forest to sparse forest in the Pan Kyu, Yang Kyng, Tar Lay, Mong Ngun, Mong Inn, Nam Hkat, Mong Pang (middle) village tracts. Changes from sparse forest to bare land was found in the village tracts of Pang Mat, Yang Kying, Mong Inn, Nam Hkat, Mong Pang (middle). Similarly, conversion from bare land to agriculture land was existed in the Pang Mat, Kat Taung, Kat Hpa, Mong Lan, Mong Ngun, Mong Naw/ Hpar Ta, Loi Mway, Mong Zin, Yang Hka, Mong Pat (Upper), Nam Lin village tracts. Moreover, the changing pattern from water-body to sparse forest was broadly seen in the Yang Law, Wut Sawng, southern Kat Taung, western Kat Hpa, western Mong Lan, north-western Mong Lat and central Mong Zin village tracts. The changes area of agriculture land to sparse forest and build-up area to agriculture land were not found distinctly in the specific area of the village tracts, because these areas are distributed around the township with a few amounts.

By comparing the two maps (2011 and 2021) during ten years period (Figure 4), there are three types of changes in LULC classes which is found in the research area: the positive change, negative change and stable or no change area. To be seen clearly, those changes were labelled with colour signs: positive change with red colour circle, negative change with blue colour circle and no change with white colour circle which displays on the map.

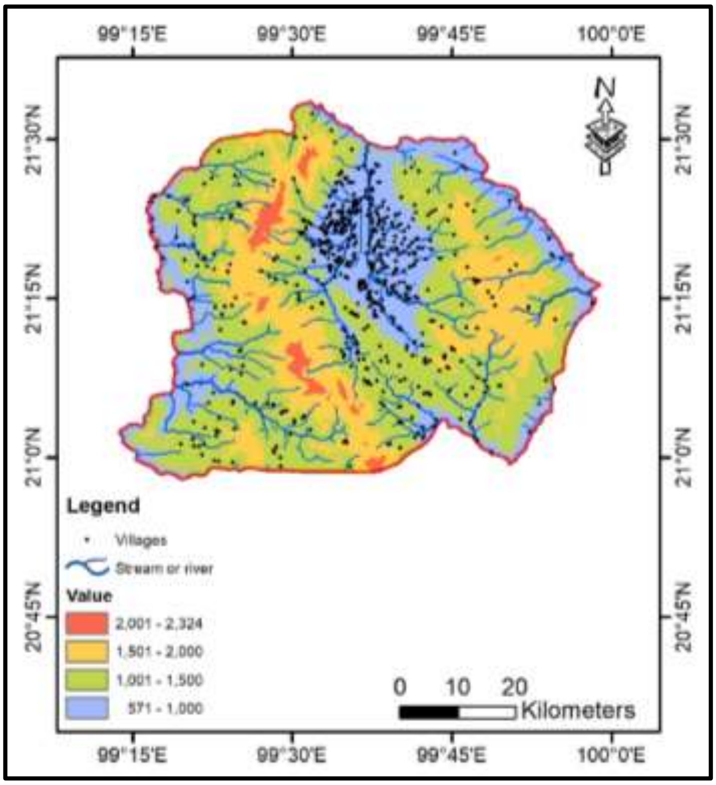


Source: Landsat 5 and Landsat 8

Figure 4 LULC Change Area in Kyaing Township (2011 and 2021)

Spatially, the **positive change** area was distinctly found in the southeast portion of Kyaing Tong Plain (Figure 4) which indicates as red colour circle. Those area was converted **from bare land to agriculture land**. In addition, the **negative changes** areas were prominently found in the southwest most and north western section of the study area (Figure 4) with blue colour circle. It was discovered **the transition from dense forest to sparse forest area**. Lastly, **no change** areas were found in the western of Kyaing Tong Plain and in the eastern peripheral area of its township (Figure 4 and 5). This area shows white colour circles and specifically found as **dense forest area**. In the stable area, villages and settlement area is not found in the higher elevation and rugged ranges region. The elevation between 1000 and 1500, 1501 and 2000 meters is rare found settlement settle area. Moreover, the altitude above 2001 meter is not found any villages in the study area (Figure 5).

However, the most notice one in the whole study area is **black colour circle**. It can be <u>illusioned that the conversion area from water-body (Figure 4_2011) to sparse forest as well as agriculture land (Figure 4_2021).</u> Actually, those area was just concerned about temporal acquiring satellite images because the heavy rainfall was gathered in the area and appeared as water-body and disappeared in 2021.



Source: Landsat 5 and Landsat 8

Figure 5 Relief and Drainage Pattern in Kyaing Township

Volume of Change

During a decade, the changes trends were both to be increased and decreased with some extent amount. In order to know clearly, it has been examined by using Volume of Change Method (Jasbir Singh and Dhillon, 2004), based on the attribute data provided by the Landsat (Table 7 and Figure 6).

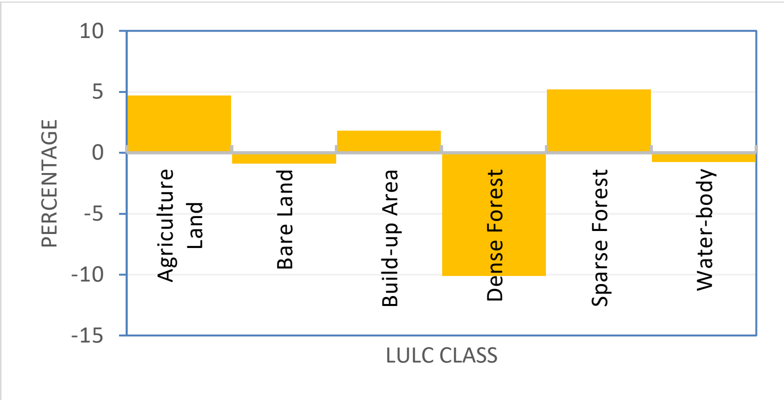
Due to the population increased and their activities year after year, the area of LULC classes would be changed from one class to another. The increased categories or positive change area were agriculture land with 4.72 percent build-up area with 1.81 percent (26.45 sq. mi) and sparse forest with 5.21 percent during 2011-2021year period. On the other hand, the decreased LULC classes or negative changes were bare-land 0.89 percent, dense forest 10.1 percent and body with 0.75 percent.

The notable increased volume of change 5.21% is the sparse forest from 48.58% in 2011 to 53.80% in 2021 because of the population growth (Table 7, Figure 6 and Figure 7). They are utilized dense forest for their likelihood and socio-economic development. Thus, the vast area of dense forest is degraded and transformed into sparse forest in a decade. Conversely, the distinguishable decreased volume of change 10.1% is dense forest from 28.56% in 2011 to 18.46% in 2021 due to human behaviour as well (Table 7, Figure 6 and Figure 7).

Table 7 Changes of LULC Category by Percentage in Kyaing Tong Township

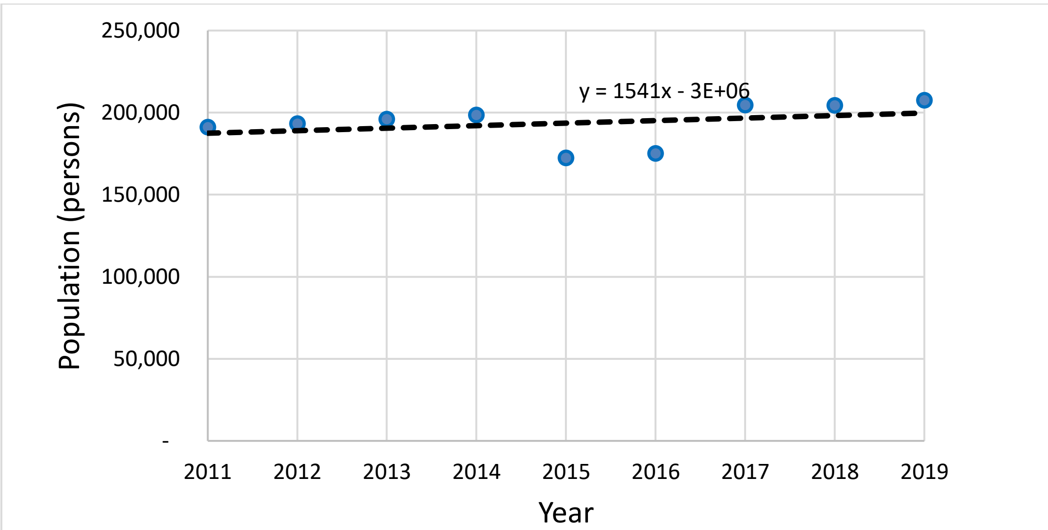
No.	Category	2011 Area (%)	2021 (Area (%)	Volume of Change (±)
1	Agriculture Land	9.28	13.99	4.72
2	Bare Land	9.14	8.26	-0.89
3	Build-up Area	2.23	4.04	1.81
4	Dense Forest	28.56	18.46	-10.10
5	Sparse Forest	48.58	53.80	5.21
6	Water-body	2.20	1.45	-0.75
	Total	100.00	100.00	

Source: Based on Table (5)



Source: Based on Table (7)

Figure 6 Volume of LULC Change in Kyaing Township



Source: General Administrative Department, Kyaing Tong

Figure 7 Changes of Population in Kyaing Tong Towhship

Conclusion

LULC is the most prominent configuration of the environmental change phenomenon occurring at spatial and temporal scales. This research is conducted to identify the LULC changes pattern in the two time-frames of 2011 and 2021 in Kyaing Tong Township. LULC classes had been produced on the basic of remote sensing Landsat data sources. In the accuracy validation process, the remote sensing images and ground truth data were compared and checked to be consistent with those sources of data. Then, the tabulation of accuracy assessment by Kappa coefficient was resulted with almost perfect agreement of 85.92%.

The distribution pattern of LULC classes between 2011 and 2021 were found the same trend of area in extent. The greater to smaller size of dispersion in those classes were sparse forest, dense forest, agricultural land, bare land, built-up area and water-body. The largest and smallest area in 2021 were sparse forest (53.8%) and water body (1.45%).

In the arrangement of change matrix grid cell, the proportion of change and no change area were portrayed 39.7% (1,501.96 sq. km) and 60.3% (2,281.35 sq. km) in the study area. Similarly, the volume of change method had been described both increased and decreased: the increased categories were agriculture land, build-up area and sparse forest whereas, the decreased one were bare land, dense forest and water-body.

In the entire township, the most remarkable change area on the map is virtually noticed as water-body because water-body area is gathered only in the compact place whereas the other changes area (e.g., dense and sparse forest) is scattered to the whole study area, it is not prominent even though the amount of change is much more than water body area. The greater area loss of changes, such as dense forest to sparse forest, bare land to agriculture land, were indicated the result of population growth and their socio-economic activities. Hence, proper management in the study area might be required for the sustainable development and avoided improper resources use.

Thus, land use and land cover change by using RS/GIS are of vital useful and helpful for the researcher and planners for the better future plans in resource-used management in the era of information technology.

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